ECONOMIC IMPACTS OF CLIMATE CHANGE ON CALIFORNIA AGRICULTURE

A Paper From:
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Prepared By:
Christopher J. Costello, Olivier Deschênes, and Charles D. Kolstad

University of California, Santa Barbara

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Preface

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In 2003, the California Energy Commission's PIER Program established the **California Climate Change Center** to document climate change research relevant to the states. This center is a virtual organization with core research activities at Scripps Institution of Oceanography and the University of California, Berkeley, complemented by efforts at other research institutions. Priority research areas defined in PIER's five-year Climate Change Research Plan are: monitoring, analysis, and modeling of climate; analysis of options to reduce greenhouse gas emissions; assessment of physical impacts and of adaptation strategies; and analysis of the economic consequences of both climate change impacts and the efforts designed to reduce emissions.

The California Climate Change Center Report Series details ongoing center-sponsored research. As interim project results, the information contained in these reports may change; authors should be contacted for the most recent project results. By providing ready access to this timely research, the center seeks to inform the public and expand dissemination of climate change information, thereby leveraging collaborative efforts and increasing the benefits of this research to California's citizens, environment, and economy.

For more information on the PIER Program, please visit the Energy Commission's website www.energy.ca.gov/pier/ or contract the Energy Commission at (916) 654-5164.

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Abstract

Using county-level data from the United States Department of Agriculture's Census of Agriculture, this study evaluates the effect of weather and climate on agricultural profits in the State of California. The approach is to estimate revenue less production cost per acre as a function of land characteristics, weather realizations, and climate. This model is then used to evaluate the effect of two scenarios of climate change for the California over the coming century. Generally, we find that climate change does not have a negative effect on agricultural profits. There are significant caveats to this result, such as keeping water supply and farm prices constant.

Keywords: Climate change, California, agriculture, profits, degree-days

1.0 Introduction

California is at the forefront of states and even countries in having legislation on the books mandating the reduction of greenhouse gas emissions by a specified amount for specific dates. One reason for this aggressiveness is the perceived vulnerability of the state to climate change. As one example, climate change threatens to disrupt the state's precious freshwater supply, which relies heavily on snowfall and snowmelt from the Sierra Nevada mountains. Climate change also threatens one of the state's most important industries: agriculture.

This paper addresses the question of how agriculture in the state may be affected by a change in climate. To answer this question, we look at two factors influencing farm profits: (1) how farm profit differs from one county to another in the state, inferring the effect climate has on those differences; (2) how farm profit differs for a county from one year to the next, as weather turns out to be different that expected. Statistically combining these two dimensions of the problem allows us to infer how climate and weather affect profits and, in turn, how a changed California climate may affect agricultural profits.

We then use our statistical model, estimated on historic data, to forecast agricultural profits in the state under two scenarios of global climate change projected down to the state level: one business-as-usual (A2) and the other a more moderate scenario (B1). These scenarios were developed for the Intergovernmental Panel on Climate Change (IPCC) and are widely used.

Our qualified conclusion is that agricultural profits would appear to be positively affected by climate change, though specific crops may be very negatively affected. The crops most negatively affected are table grapes and some citrus.

In the next sections we develop our model and discuss data sources. We then turn to our results.

2.0 Background

A number of authors consider the effect of climate change on agriculture. Early work (i.e., from the early 1990s) focused on process models. Adams (1989), Adams et al. (1990), and Rosenzweig and Parry (1994) are prominent examples of the use of agricultural process models (including crop growth models) to measure the effect on crop yields of climate change. These models are typically physiological with limited scope for endogenous farmer behavioral response to climate change. Typically, adaptation and adjustment are absent or exogenous.

Some crop growth models allow a certain amount of farmer adaptation to climate change. For instance, Kaiser et al. (1993) use a simulation model to forecast a century of effects from a gradual change in the climate. Their model assumes farmers choose which variety of crop would have done best in the previous (simulated) decade. In this way, some adaptation over time is represented in their model. This results in considerably less loss from a doubling of carbon dioxide concentrations (Schimmelpfennig et al. 1996).

Hansen (1991) suggests that crop growth models (which must enumerate substitution possibilities) may miss some of the substitution opportunities available to farmers. He estimates a cross-sectional model of corn production in the United States where expected climate (July mean temperature and precipitation) as well as realized weather are used to explain cross-sectional variations in corn yield. His results for a temperature increase are mixed, showing yield increases in some climates and yield decreases in others.

Similar information can be derived statistically from observations on agricultural output. Perrin and Smith (1990) investigate the effect of weather on several crops in North Carolina and then use results of climate models to estimate the effect of climate change on crops. Hansen (1991) estimates the effect of weather and climate on corn yield and then postulates the effect of a change in climate. Some studies in agricultural economics and agronomy focus more directly on the weather effect (Kaylen et al. 1992; Thompson 1986; Wescott 1989; Kaufmann and Snell 1997). These models approach the problem after the production decisions have been made, only considering the effect of actual weather realizations on yield. Typically the weather data is transformed into some measure of deviation from expected weather. The underlying idea is that the effect of normal weather (represented by climatic expectations) is captured in the farmer's cropping practices, but that unusual weather will have an impact of yield. Of particular note to California is the recent work of Lobell et al. (2007), relating climate to yields of a number of specific California-relevant crops (using data from California).

Mendelsohn et al. (1993, 1994) introduced the "Ricardian" approach to econometrically estimating the effect of climate on farm output (though this approach can be traced back to Johnson and Haigh 1970). The central idea of Mendelsohn et al. (1993, 1994) is to measure the differences in land values across the United States, inferring that land value differences are due to endowed soil quality and climate. This allows the authors to infer the value of different climates. Using this approach, they infer a very small effect (possibly positive, possibly negative) on U.S. agriculture from climate change. Schlenker et al. (2005, 2006) have performed a similar analysis on a subset of the United States, focusing on non-irrigated land. In recent work, Schlenker et al. (2007) have focused on sub-county data in California producing interesting results on long-run effects of climate on land values and water availability.

As Schlenker et al. (2005) argue, irrigation is an important issue in the West. But it is not as simple as one might expect. McFadden (1984) focuses on how a farmer (or other agent) may change behavior based on uncertainty about climate change (or even weather variability). In essence, if the farmer feels a possibility of climate change exists, he may adopt more robust practices (such as irrigation) that perform relatively well over a range of weather or climates, sacrificing a bit relative to the case of perfect knowledge about the weather. Fisher and Rubio (1997) similarly find that water storage investments should increase as the variance of precipitation increases.

The main appeal of the Ricardian approach is that if land markets are operating properly, prices will reflect the present discounted value of land rents into the infinite future. Thus the hedonic approach promises an estimate of the effect of climate change that accounts for the adaptation behavior that undermines the earlier work based on process models. However, to successfully implement the hedonic approach, it is necessary to obtain econometrically consistent estimates of the independent influence of climate on land values, and this requires that all unobserved determinants of land values are uncorrelated with (orthogonal to) climate. Deschênes and Greenstone (2007) demonstrate that temperature and precipitation means covary with soil characteristics, population density, per capita income, and latitude. Moreover, Schlenker, Hanemann, and Fisher (2005) show that the availability of irrigated water also covaries with climate (Schlenker, Hanemann, and Fisher 2005). This means that functional form assumptions are important in the hedonic approach and may imply that unobserved variables are likely to covary with climate. Further, recent research has found that cross-sectional hedonic equations appear to be plagued by omitted variables bias in a variety of settings (Black 1999; Black and Kneisner 2003; Chay and Greenstone 2005; Greenstone and Gallagher 2005). Overall, it may be reasonable to assume that the cross-sectional hedonic approach confounds the effect of climate with other factors (e.g., soil quality).

Kelly et al. (2005) extend the Ricardian approach by distinguishing between expected weather (climate) and the actual weather than is realized during a growing season. Expected weather determines crop choice and similar decisions; what weather is actually realized determines actual profits. They thus provide one of the first analyses of how total farm profits are affected by both climate and by weather shocks (deviations of weather from what is expected). Rather than examine a single time-slice of farm land values (a cross-section), they examine a pooled time-series cross-section of thirty years of farm profit data at the county level, though just for the Midwest of the United States (not the entire country). Their results are consistent with those of Mendelsohn et al. (1993, 1994) regarding the long-run cost of climate change. But they also explore how increased extreme weather events may increase the cost of climate change, over and above the costs associated with a change in the mean weather.

One problem with the Kelly et al. (2005) approach (in addition to its only covering the Midwest) is the treatment of unobserved farm characteristics that can play an important role in determining profits. Deschênes and Greenstone (2007) address this and other issues in their use of the profit function approach to measuring the effect of climate and weather. For one thing, their analysis involves the entire United States as well as individual states. In addition, they cleverly include climate as a county-level fixed effect, which permits them to focus on the effect of weather on farm profits. Although this provides a better estimate of profits, it is not possible to disentangle the effect of climate from other unobserved determinants of profits, since all are included in the fixed effect. Thus it is difficult to use their model to evaluate the effect of a counterfactual climate change. They suggest that focusing only on weather provides a conservative estimate of the effect of climate on profits.

3.0 Methodology

Our approach is to use county-level data in California over a twenty year period to understand how climate and weather affect farm profits and crop yields. We then use this estimated relationship to simulate how a changed climate might affect farm profits and yields.

3.1. Introducing Weather

The canonical estimating equation involving weather (W) but not climate is of the form:

$$(1)\quad y_{ct} = \alpha_c + \lambda_t + X_{ct}\theta + \sum_{k=1}^{K} \beta_k W_{kct} + \varepsilon_{ct}$$

where the indices *c* and *t* denote county and year, respectively, and *k* represents different measures of weather (such as annual average temperature or annual total precipitation). In the models of agricultural profits the dependent variable is expressed in dollars per acre of farmland, while in the models for crops it is expressed in value of production per acre planted. In both cases nominal dollars are converted to 2006 dollars. The key variables of interest in Equation 1 are the *W* variables for different k's, which represent degree-days and precipitation in a county c and year t. As mentioned, the "k" index simply denotes the various measures of degree-days and precipitation we control for (e.g., winter degree-days, spring degree-days, etc).[1] In different versions of (1), we examine weather variables from both a seasonal perspective and an annual perspective.

Equation 1 also includes a full set of county fixed effects, α_c. The appeal of including the county fixed effects is that they absorb all unobserved county-specific time invariant determinants of the dependent variable. For example, to the extent that agricultural soil quality is constant over time, the county fixed effects will account for differences in soil quality across counties. As such, the inclusion of county fixed effects will help mitigate the problem of omitted variables bias that has plagued some of the previous literature. Variants of this approach have been used in Deschênes and Greenstone (2007) and Schlenker and Roberts (2008).

The model above also includes a full set of year fixed effects, λ_t, that control for annual differences in the dependent variable that are common across counties. In particular the year fixed effects will capture the impact of changes in commodity prices on profits or value of production. An alternative is to directly control for prices, like in Kelly, Kolstad, and Mitchell (2005). The variables in the vector X_{ct} are the soil quality variables we described earlier. These variable change a little (but not much) from one year to another. Finally, the last term in Equation 1, ε_{ct}, is a statistical error term.

3.2. Controlling for Climate

In the spirit of Kelly, Kolstad, and Mitchell (2005), we augment Equation 1 to include proxies for farmer's expectations about weather. Viewing the climate as average weather, or more specifically, the distribution of weather, we control for expected climate. While expectations are not directly observed, we assume that expectations are derived from observing past weather. Specifically, we calculate the 30-year running average of the weather variables and include them in Equation 1, in addition to the realized degree-days and precipitation for a given year. Given the inclusion of county fixed-effects in Equation 1, the statistical identification of the augmented equation requires that climates are "changing" in the sense that the 30-year running averages must be time-varying (otherwise these variables would be perfectly collinear with the county fixed effects). Figure 1 reports the trends in the annual realization of the degree-days variable and its 30-year running average (starting in 1950). There are two key points: Average annual degree-days exhibit important year-to-year variation, ranging from 2,300 to 2,900. This variation will play a key role in the statistical identification of Equations 1 and 2 below. On the other hand, the 30-year running average of degree-days evolves very smoothly over time, as was expected. Its time-series pattern shows an essentially linear increase between 1950 and 2005

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[1] We also considered models where degree-days and precipitation are modeled quadratically rather than linearly. These results were generally similar, although the statistical precision was greatly reduced.

around a mean of 2,500.[2] This pattern foreshadows the challenges in statistically identifying the "augmented" models of the form:

$$(2)\quad y_{ct} = \alpha_c + \lambda_t + X_{ct}\theta + \sum_{k=1}^{K} \beta_k W_{kct} + \sum_{k=1}^{K} \delta_k C_{kct} + \varepsilon_{ct}$$

Where $C_{kc\tau}$ denotes the average of W_{kct} over the period τ-30 to τ-1. This approach follows from Kelly, Kolstad, and Mitchell (2005).

3.3. Estimation

There are further issues about Equations 1 and 2 that require attention. First, it is appropriate to estimate the equations using weights. Since the dependent variables are expressed in dollars per acres of farmland (or acres planted), there are two reasons to weight the models by the square root of acres of farmland (acres planted). First, the estimates of the value of farmland from counties with large agricultural operations will be more precise than the estimates from counties with small operations, and this weight corrects for the heteroskedasticity associated with the differences in precision. Second, the weighted mean of the dependent variables will equal to the mean value of farmland per acre in California.

It is likely that the error terms are serially correlated over time. To account for this, we presented "clustered" standard errors, where the clusters are defined by counties. This allows for arbitrary serial correlation over time within counties.

3.4. Calculation of Impacts

Once the gradients of the profits and yield functions are estimated, it is relatively straightforward to project the impacts of climate change. We simply combine the fixed-effect regressions estimates with the projected differences in degree-days and precipitations reported in Table 1b.

[2] We note that the change in "climate" (i.e., the 30-year running average of degree-days) is not uniform across counties. On average, our measure of climate has increased by about 100 degree-days between 1950 and 2002. However some counties experienced large increases—for example Fresno and Imperial counties, where historical degree-days increased by 500 degree-days between 1950 and 2002.

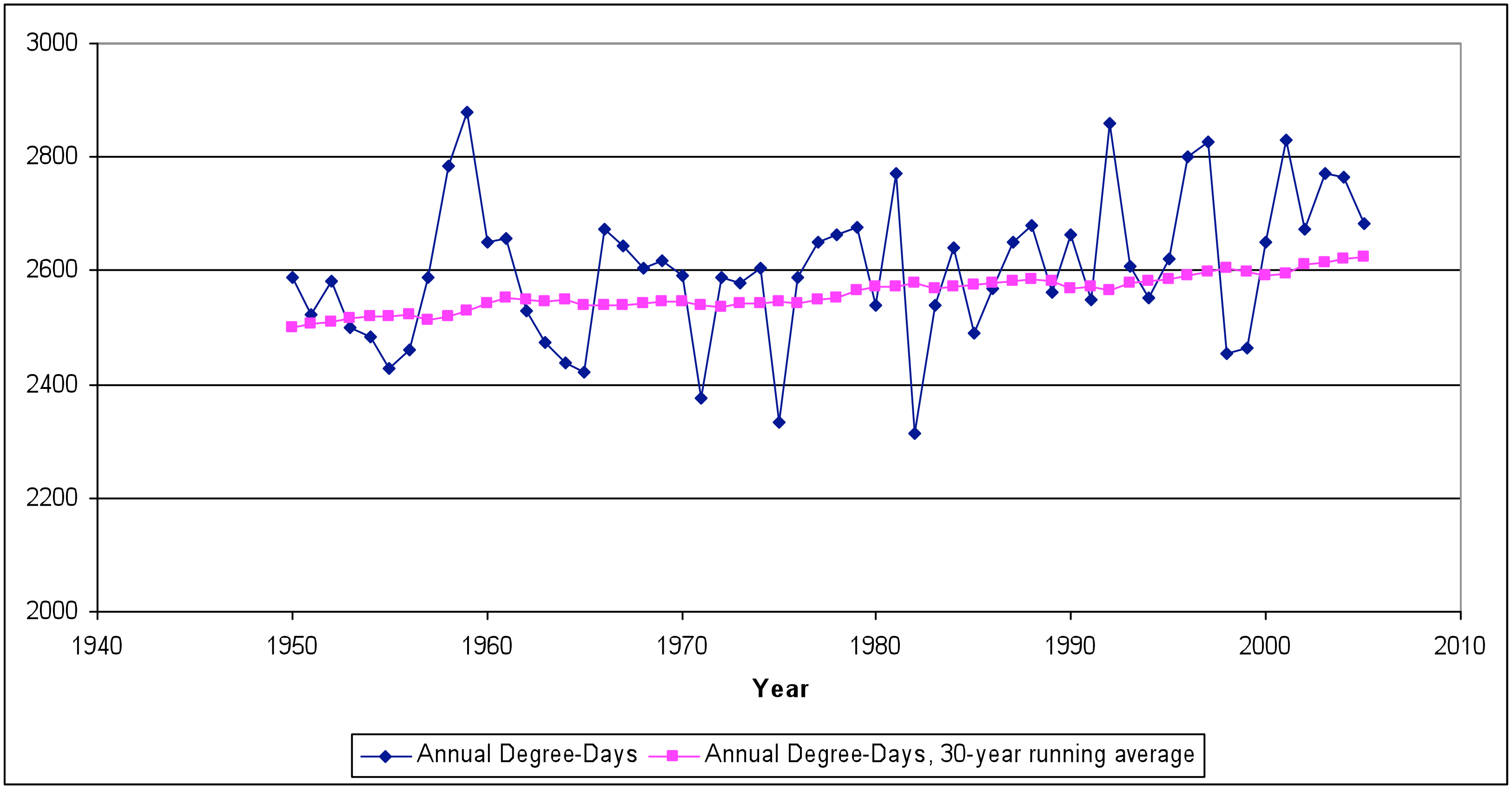

**Figure 1. Annual realization of degree-days (8°C–32°C) and its 30-year running average, averaged across California counties,
1950–2005**

Table 1a. County-level summary statistics on weather realizations and projections of future climates in California

	Actual	Projected: CCSM-B1 (Levels)			Projected: CCSM-A2 (Levels)		
	1950-2005	2010-2039	2040-2069	2070-2099	2010-2039	2040-2069	2070-2099
All Year							
Degree-Days (8-32)	2,601.5	2,765.8	2,897.6	3,016.6	2,714.5	3,096.6	3,612.3
Degree-Days (32+)	1.4	3.8	4.6	5.7	3.6	6.9	16.0
Total Precipitation (cm)	71.0	65.9	71.5	72.6	63.6	62.8	64.9
Winter							
Degree-Days (8-32)	204.6	224.4	251.1	266.2	215.6	280.5	384.7
Degree-Days (32+)	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total Precipitation	35.5	34.6	35.6	35.7	31.3	32.4	32.3
Spring							
Degree-Days (8-32)	762.1	813.8	846.4	865.2	788.2	888.8	1,049.3
Degree-Days (32+)	0.1	0.4	0.7	0.8	0.4	1.2	2.8
Total Precipitation	8.6	8.9	8.1	9.4	8.5	7.8	7.6
Summer							
Degree-Days (8-32)	1,234.4	1,313.3	1,358.2	1,401.9	1,318.9	1,416.8	1,584.6
Degree-Days (32+)	1.3	3.4	3.9	4.9	3.2	5.7	13.1
Total Precipitation	2.0	1.5	1.8	1.5	1.7	1.3	1.0
Fall							
Degree-Days (8-32)	400.4	414.3	441.9	483.4	391.8	510.5	593.6
Degree-Days (32+)	0.0	0.0	0.0	0.0	0.0	0.0	0.1
Total Precipitation	25.0	21.0	26.0	26.1	22.1	21.3	24.0
Observations	3248	1740	1740	1740	1740	1740	1740

Notes: Predictions are from the National Center for Atmospheric Research's Community Climate System Model, version 3 (CCSM3), under IPCC *Special Report on Emissions Scenarios* (SRES) scenarios B1 and A2. Calculations are based on daily record data for the period 1950–2005 and 2010–2099. Winter is defined as the first quarter of the year; the other seasons are correspondingly defined. Degree-Days 8-32 denotes Degree-Days 8°C–32°C and Degree-Days 32+ denotes Degree-Days 32°C+.

Table 1b. County-level summary statistics on predicted changes in climate in California

	Projected: CCSM-B1 (Changes)			Projected: CCSM-A2 (Changes)		
	2010-2039	2040-2069	2070-2099	2010-2039	2040-2069	2070-2099
All Year						
Degree-Days (8-32)	164.3	296.1	415.1	113.0	495.1	1,010.8
Degree-Days (32+)	3.49	4.21	5.33	3.22	6.56	15.65
Total Precipitation (cm)	-5.02	0.48	1.65	-7.35	-8.18	-6.08
Winter						
Degree-Days (8-32)	19.8	46.5	61.6	11.0	75.9	180.1
Degree-Days (32+)	0.00	0.00	0.00	0.00	0.00	0.00
Total Precipitation	-0.86	0.14	0.24	-4.18	-3.08	-3.17
Spring						
Degree-Days (8-32)	51.7	84.3	103.1	26.1	126.7	287.2
Degree-Days (32+)	0.28	0.57	0.68	0.24	1.02	2.70
Total Precipitation	0.31	-0.52	0.77	-0.06	-0.83	-0.97
Summer						
Degree-Days (8-32)	78.9	123.8	167.5	84.5	182.4	350.2
Degree-Days (32+)	2.15	2.58	3.57	1.92	4.44	11.81
Total Precipitation	-0.49	-0.17	-0.44	-0.28	-0.61	-0.94
Fall						
Degree-Days (8-32)	13.9	41.5	83.0	-8.6	110.1	193.2
Degree-Days (32+)	0.01	0.01	0.02	0.00	0.03	0.09
Total Precipitation	-3.97	1.05	1.09	-2.82	-3.65	-0.99
Observations	1740	1740	1740	1740	1740	1740

Notes: Predictions are from the CCSM3 model, under scenarios B1 and A2. Calculations are based on daily record data for the period 1950–2005, and 2010–2099. Predicted changes are obtained by taking difference between the 1950–2005 averages in realized degree-days and precipitation reported in Table 1a and the predicted levels of degree-days and precipitation reported in Table 1a. Degree-Days 8-32 denotes Degree-Days 8°C–32°C and Degree-Days 32+ denotes Degree-Days 32°C+.

We first present the calculation for the models that only control for realized weather (e.g., Equation 1). For a given climate change model/scenario, the impact for county c is given by:

$$(3)\quad IMPACT_c = ACRES_c \times \left(\sum_k \hat{\beta}_k \Delta W_{kc} + \sum_k \hat{\delta}_k \Delta C_{kc} \right)$$

Where ΔW_{kc} is the predicted change in weather variable k in county c. These changes are specific to a climate change model, scenario, and horizon (i.e., short-run, medium-run, long-run). The variables $ACRES_c$ represent the average acres of farmland (or acres planted) during the sample period in county c. We need to "reweight" the calculations since the regression models are profits per acre (and value of production per acre). Finally, to obtain the impact for the state as a whole, we simply sum the county-specific impacts ($IMPACT_c$) across counties.

4.0 Data Sources

4.1. Farm Revenues, Expenditures, and Profits

The data on agricultural finances are from the 1969, 1974, 1987, 1992, 1997, and 2002 Censuses of Agriculture. Data from the Census of Agriculture are available for 1978 and 1982, as well as for years prior to 1969. However, these data are not comparable since the production expenditure variables are not different than in the years we used. All farms and ranches from which $1,000 or more of agricultural products are produced and sold, or normally would have been sold, during the census year are required to submit a census form. For confidentiality reasons, counties are the finest geographic unit of observation that is publicly available in the Census of Agriculture.[3]

From these data we construct a variable for county-level agricultural profits per acre of farmland. The numerator is constructed as the difference between the market value of agricultural products sold and total production expenses across all farms in a county. Production expenses exclude the value of or return from land. The denominator includes acres devoted to crops, pasture, and grazing. The revenues component measures the gross market value before taxes of all agricultural products sold or removed from the farm. It excludes income from participation in federal farm programs,[4] labor earnings off the farm (e.g., income from harvesting a different field), or nonfarm sources. Thus, it is a measure of the revenue produced with the land.

Total production expenses are the measure of costs. They include expenditures by landowners, contractors, and partners in the operation of the farm business. This covers all variable costs (e.g., seeds, labor, and agricultural chemicals/fertilizers). It also includes measures of interest

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[3] We attempted to develop data at the ZIP/Postal code level but the ZIP code is for the mailing address of the farm, which may be in a totally different location from the farm. Furthermore, the United States Department of Agriculture has a policy of not releasing cost and value figures at the sub-county level, even if requested to do so on a reimbursable basis. Consequently, county-level data is the smallest geographic unit available.

[4] An exception is that it includes receipts from placing commodities in the Commodity Credit Corporation loan program. These receipts differ from other federal payments because farmers receive them in exchange for products.

paid on debts and the amount spent on repair and maintenance of buildings, motor vehicles, and farm equipment used for farm business. Its main limitation is that it does not account for the rental rate of the portion of the capital stock that is not secured by a loan, so it is only a partial measure of farms' cost of capital.[5] Just as with the revenue variable, the measure of expenses is limited to those that are incurred in the operation of the farm so, for example, any expenses associated with contract work for other farms is excluded.[6]

4.2. Crop Production and Yields

Annual county-level data on production, value of production, and acres planted for the period 1980–2005 were taken from the County Agricultural Commissioners Data.[7] This summary, which is published annually, is based on the annual Crop Reports compiled by the California County Agricultural Commissioners. These reports provide the most detailed annual data available on agricultural production by county. Basic data collected by the Agricultural Commissioners and their staffs are compiled from many sources. Sources vary from county to county. Examples of data sources include growers' surveys, regulatory and inspection data, shipment data, and industry assessments. Price data reflect the average price received by growers, except fresh market fruits and vegetables, which are on a packed and ready-to-ship basis.

4.3. Soil Quality Data

Like most previous analyses, we rely on the National Resource Inventory (NRI) for our measures of soil quality and characteristics. The NRI is a massive survey of soil samples and land characteristics that is conducted in census years. We follow the convention in the literature and use a number of soil quality variables as controls in the equations for profits and yields, including measures of susceptibility to floods, soil erosion (K-Factor), slope length, sand content, irrigation, and permeability. County-level measures are calculated as weighted averages across sites used for agriculture, where the weight is the amount of land the sample represents in the county. Although these data provide a rich portrait of soil quality, we suspect that they are not comprehensive. To this end, we consider models that include county fixed effects to capture these effects.

4.4. Historical Weather Data

The weather data are drawn from the National Climatic Data Center (NCDC) Summary of the Day Data (File TD-3200). The key variables for our analysis are the daily maximum and

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[5] In particular, interest payments are the only measure of the rental cost of capital in the censuses. Thus, our measure understates the cost of capital by not accounting for the opportunity cost of the portion of the capital stock that is not leveraged. Further, our measure of agricultural profits does not account for labor costs that are not compensated with wages (e.g., the labor provided by the farm owner).

[6] The censuses contain separate variables for subcategories of revenue (e.g., revenues due to crops and dairy sales), but expenditures are not reported separately for these different types of operations. Consequently, we cannot provide separate measures of profits by these categories and instead focus on total agriculture profits.

[7] National Agriculture Statistics Service, County Agricultural Commissioners' Data. www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/indexcac.asp

minimum temperature, as well as the total daily precipitation for the period 1920–2005. To ensure the accuracy of the weather readings, we developed a weather station selection rule. Specifically, we dropped all weather stations that were not operating consecutively for a full year, though we allow stations to enter and exit the sample over time. The acceptable station-level data is then aggregated at the county level by taking an inverse-distance weighted average of all grid points that lie within 200 kilometers (km) of each county's centroid.

With this data at hand, we now have a complete daily time-series starting January 1, 1920, and ending December 31, 2005, for every county in California, with valid measurements for daily minimum and maximum temperature, and total precipitations. We use the daily data to construct measures of "exposure" that follow from the agronomic literature. Agronomists have shown that plant growth depends on the cumulative exposure to heat and precipitation during the growing season. As such, monthly average temperatures may be poor predictors of agricultural outputs since they do not capture nonlinearities, and the differential impact of exposure across the temperature distribution.

The standard agronomic approach for modeling temperature is to convert daily temperatures into degree-days, which correspond to heating units (Hodges 1991; Grierson 2002). It is likely that the effect of heat accumulation is nonlinear since temperature must be above a threshold for plants to absorb heat and below a ceiling as plants cannot absorb extra heat when temperature is too high. These thresholds or bases vary across crops, but we follow Ritchie and NeSmith's (1991) suggested characterization for the entire agricultural sector and use a base of 8° Celsius (C) (46°F) and a ceiling of 32°C (90°F). Specifically, the degree-days variable is calculated so that a day with a mean temperature: below 8°C contributes 0 degree-days; days between 8°C and 32°C contributes the number of degrees C above 8 degree-days; above 32°C contributes 24 degree-days.

Since California's climate allows certain plants to grow across the whole year, we control for heat exposure and precipitation during the course of the full calendar year. Rather than focusing on the "traditional" growing season (April to September), we construct measure of degree-days for the four quarters of the year (termed winter, spring, summer, and fall) and use these variables in some of our models for agricultural profits and yields. We also construct similar measures for total precipitations by season. The advantage of having separate variables for each season rather than cumulative ones is that it will track better the specific timing of planting and harvesting of various crops. For example, broccoli is grown all year round while navel oranges are grown from January to June. To ease comparisons with other studies, we also consider annual measures of degree-days and precipitation.

Ritchie and NeSmith (1991) also discuss the possibility of a temperature threshold at 34°C, above which increases in temperature are harmful. In addition, Schlenker and Roberts (2008) also propose other definitions of "harmful" degree-days. We consider this possibility by including in all models a variable for degree-days of base 32°C, without an upper limit. This variable will in effect allow the effect of degree-days on agricultural output to vary depending on its location in the temperature distribution.

4.5. Climate Change Predictions

In this report we estimate the effect of climate change on agriculture using climate change predictions from the National Center for Atmospheric Research (NCAR) Community Climate

System Model (CCSM), based on scenarios B1 and A2. These IPCC scenarios are derived from "storylines" that describe the relationships between the forces driving greenhouse gas and aerosol emissions and their evolution during the twenty-first century for large world regions and globally. Each storyline represents different demographic, social, economic, technological, and environmental developments that diverge in increasingly irreversible ways. The A2 storyline and scenario family is characterized with a very heterogeneous world with continuously increasing global population and regionally oriented economic growth ("business as usual"). The B1 storyline and scenario family features a convergent world with the same global population as in the A1 storyline but with rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. As such, temperature increases in the B1 scenario are more moderate than in the A2 scenario.

The model's prediction are then adjusted for bias correction and are spatially downscaled (BCSD) to the level of California counties.[8] The models provide us with daily minimum and maximum temperature and precipitation predictions at several grid points throughout California for the period 1950–2099. The grid point data produced by the CCSM model are assigned to counties by taking an inverse-distance weighted average of all grid points that lie within 100 km of each county's centroid. From the daily prediction data we can compute the same degree-day variables as we construct and analyze using the historical record period 1950–2005. The description of these variables is discussed above.

4.6. Summary Statistics

Table 1 reports the averages (across counties and years) of the seasonal degree-days and precipitation variables. For convenience, the annual averages are also reported. The "Actual" column shows the 1950–2005 averages of each of the listed variables for the 58 counties in California. Ideally these would be computed as weighted averages, where the weight would be given by acres of farmland. Unfortunately, acreage data are not available for all years, so the statistics reported are simply unweighted. The entries reveal that on average, the typical California county receives 71 centimeters (cm) of rain during the course of the year and about 2,600 degree-days between 8°C and 32°C. In addition, the typical county faces 1.4 potential harmful degree-days (those defined with base 32°C), although there is variation in this level across counties. Clearly, the distribution of degree-days and rainfall is not uniform across the year: Most of the rainfall (e.g., 61 out of 71 cm) occurs in the winter and fall months, and half of the degree-days are in the summer months.

The "Projected" columns show the values for the degree-days and precipitation variables associated with the CCSM model, under scenarios B1 and A2. Averages are reported for three time periods: the short-run (2010–2039), the medium-run (2040–2069), and the long-run (2070–2099). The entries are simple averages over the 58 counties in California, over the 30 years in each period. As stated before, the scenarios vary in their predictions of future climates.

According to the B1 scenario, the data shows that the average county in California is projected to receive an additional four hundred 8°C–32°C degree-days and 1.7 additional centimeters of

[8] Estimates are reported at: http://tenaya.ucsd.edu/wawonat/ipcc4/downscaled/bcsd/sresa2/daily/cnrmcm3/.

rain during the course of the typical year by the end of the century. The predictions under scenario A2 are more marked: The model predicts that the typical county will receive 3,600 degree-days (8°C–32°C), 16 degree-days (base 32°C), and 65 centimeters over the course of a year, on average, between 2070 and 2099. The increase in 8°C–32°C degree-days is large, representing almost a 40% increase relative to the 1950–2005 baseline. The reduction in annual precipitation is of smaller magnitude, at 8%.

It is worthwhile to emphasize that the changes over time are not monotonic. For example, the B1 scenario initially is associated with reduction in annual precipitations (e.g., in the 2010–2039 period), followed by an increase in the following years. Figure 1 shows the annual averages of precipitations and degree-days over the 2010–2099 period for both scenarios.[9] Figure 2a shows the trends in annual degree-days (8°C–32°C) for CCSM B1 and A2. As indicated in Table 1, A2 is associated with larger increases in temperature. However, most of the disparity in the predictions occurs beyond 2050. A similar pattern is observed in Figure 2b, which shows trends in annual degree-days exceeding 32°C. Finally, the patterns for annual precipitation, showed in Figure 2c, are much noisier, and as such it is difficult to see any significant difference between the scenarios.

Returning to Table 1, it is also informative to consider seasonal disparities in the climate change predictions. Both models show an increase in degree-days in all seasons, with the largest proportionate increases typical in the fall and winter months (although in absolute terms the summer month will gain the most degree-days). Again, the patterns for seasonal precipitations are less clear-cut. The A2 scenario predicts less precipitation in all seasons by the end of the century, with the largest proportionate declines in the summer months. The corresponding long-run prediction of the B1 scenario is a small increase in seasonal rainfall, except during the summer months. To the extent that various crops are more or less dependent on seasonal degree-days or rainfall, the impact of climate change on California's agriculture is likely to be very heterogeneous across crops.

[9] For better clarity, the annual averages are smoothed using a moving average.

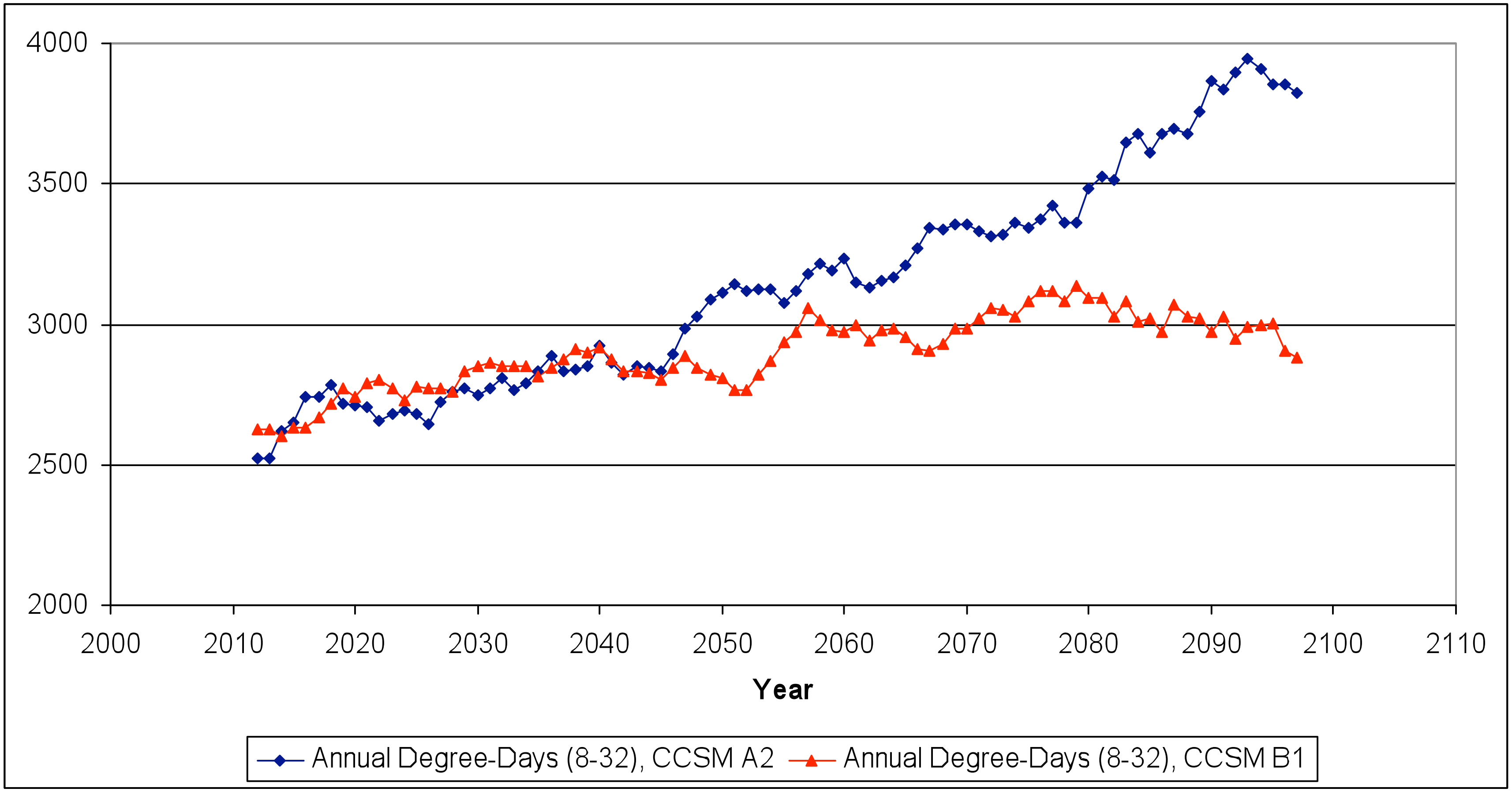


Figure 2a. Predicted annual degree-days (8°C–32°C), average across California counties, 2010–2099, scenarios B1 and A2

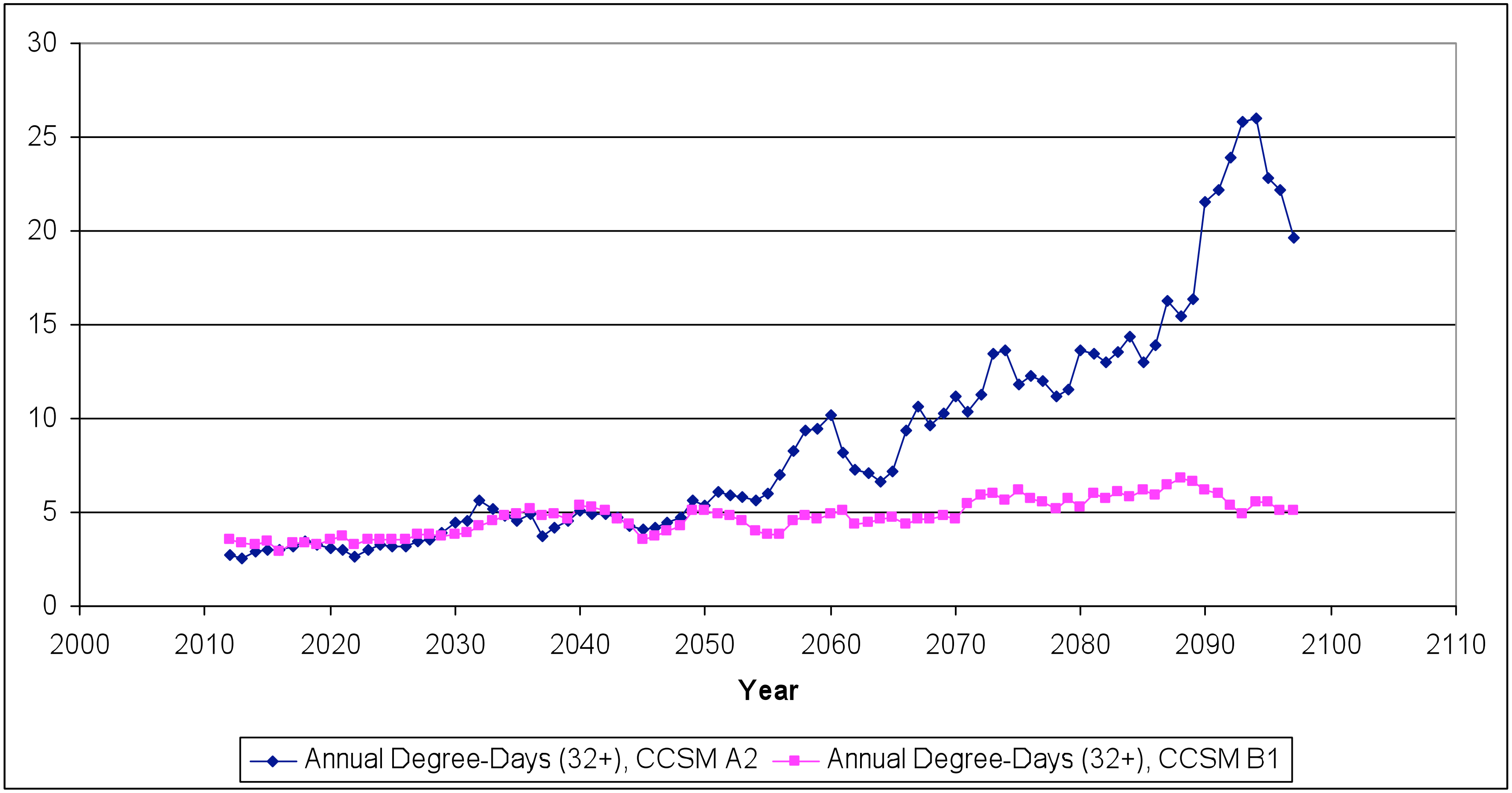


Figure 2b. Predicted annual degree-days (32°C+), average across California counties, 2010–2099, scenarios B1 and A2

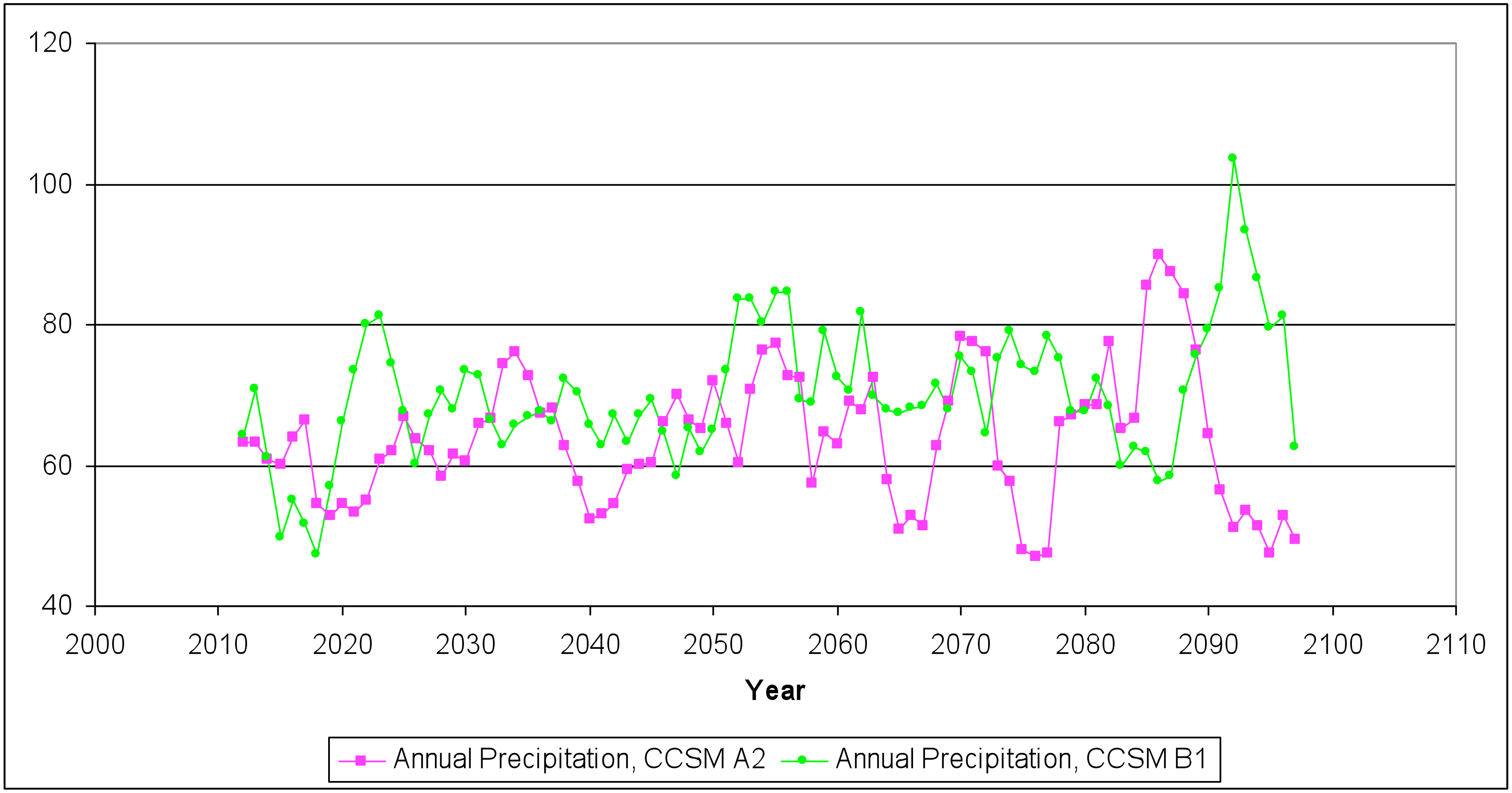


Figure 2c. Predicted annual precipitation, average across California counties, 2010–2099, scenarios B1 and A2

Figures 2a and 2b offer some information about the geographical distribution of the predicted changes in California's climate. Each figure shows the percentage change (relative to the 1950–2005 baseline) in annual degree-days (8°C–32°C) and precipitation for each county in California. The changes are calculated off the average long-run predictions (i.e., 2070–2099) for both scenarios. Figure 3a pertains to degree-days, while Figure 3b pertains to annual precipitations. It is apparent in both figures that climate change will not be uniform across counties. For annual degree-days, most counties will experience a 25% to 50% increase (CCSM3-A2). Interestingly, the five leading counties in terms of agricultural profits (Fresno, Monterey, Tulare, Kern, and San Joaquin) fall into that category, rather than the most extreme category (increases of 50% to 90%). The counties that are predicted to have the largest percentage increase in annual degree-days are: Madera, Merced, Sacramento, Placer, Nevada, Sutter and Yuba. In terms of precipitation, most counties are predicted to experience a smaller percentage decline (-10% or more). Importantly, it appears again the leading counties in terms of profits are predicted to suffer the least reduction in annual rainfall.

Table 2 presents summary statistics about the financial activities of farms in California. These data are taken from the 1969–1974 and 1987–2002 Censuses of Agriculture. Averages are calculated separately for each year across the 58 counties of California. The top panel shows state totals, while the bottom panel reports county averages. The first row shows the total farmland acreage has been steadily declining over time, from 35.7 million acres to 27.6 million. Total profits (defined as revenues minus production expenditures) fluctuate over time with no clear trend, around an average of $4.7 billion (in 2006 dollars). Similar patterns are observed in the county-level averages: Profits were the highest in 1997, at $127 million and the lowest in 1969 at $32 million, on average per county. In terms of profits per acre, the average over the census years is $160 dollar per acre farmed, with a peak of $271 in 1997.

Finally, Table 3 reports averages for production and yields of the 15 largest value crops in California over the 1980–2005 period. For this analysis, greenhouse production was omitted as it is less clear how climate change will affect this type of production. The crops are listed alphabetically in the first row. Importantly, some of these crops are perennial (almonds, avocados, grapes, lemons, oranges, pistachios, and walnuts) and annuals (broccoli, hay, lettuce, strawberry, and tomatoes). We will investigate the possibility of differential impacts across annuals and perennials in future work.

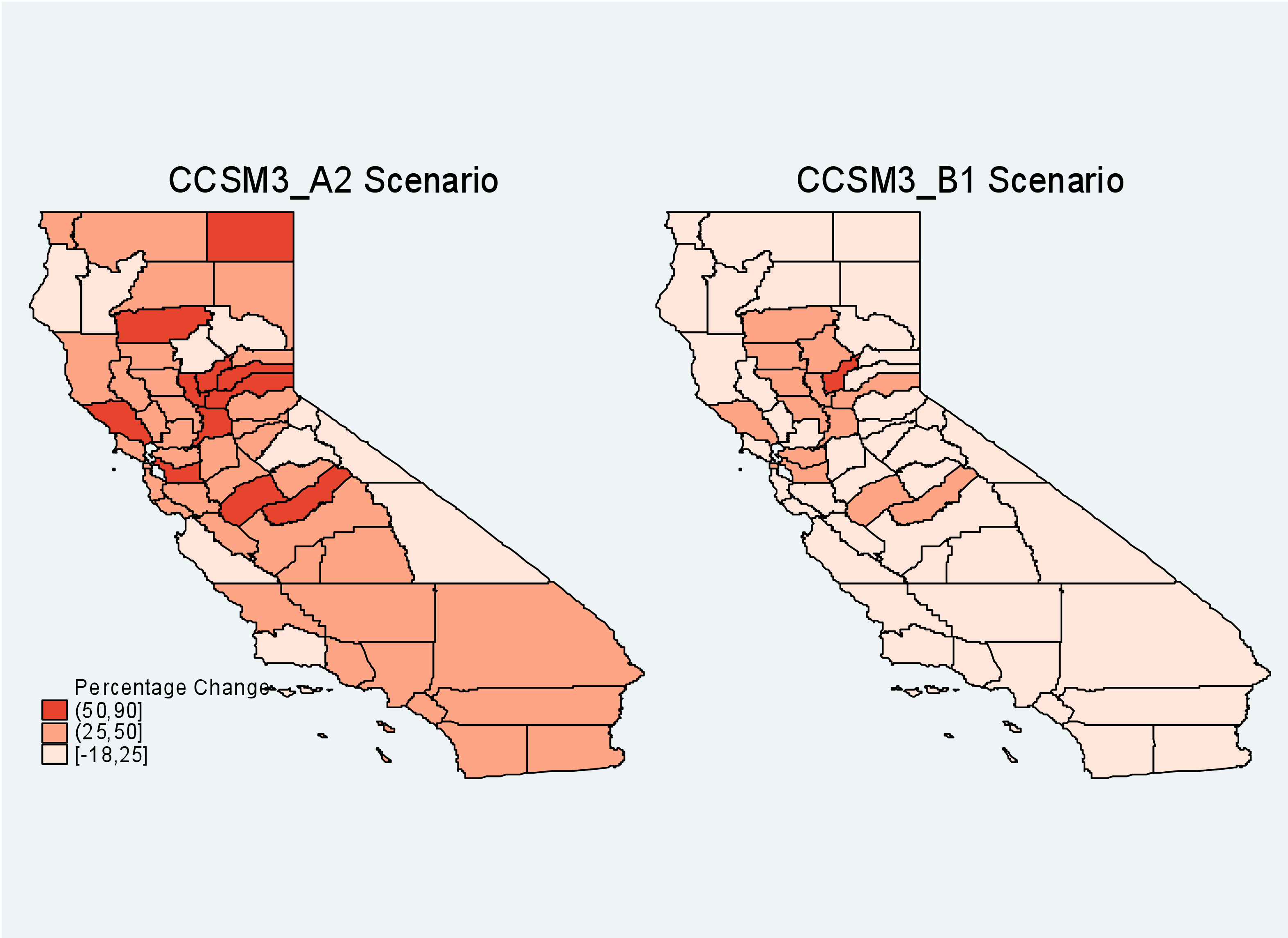

CCSM3_A2 Scenario
CCSM3_B1 Scenario
Percentage Change
(50,90]
(25,50]
[-18,25]

Figure 3a. Predicted change in annual degree-days, percentage change in 2070–2099 relative to the 1950–2005 baseline

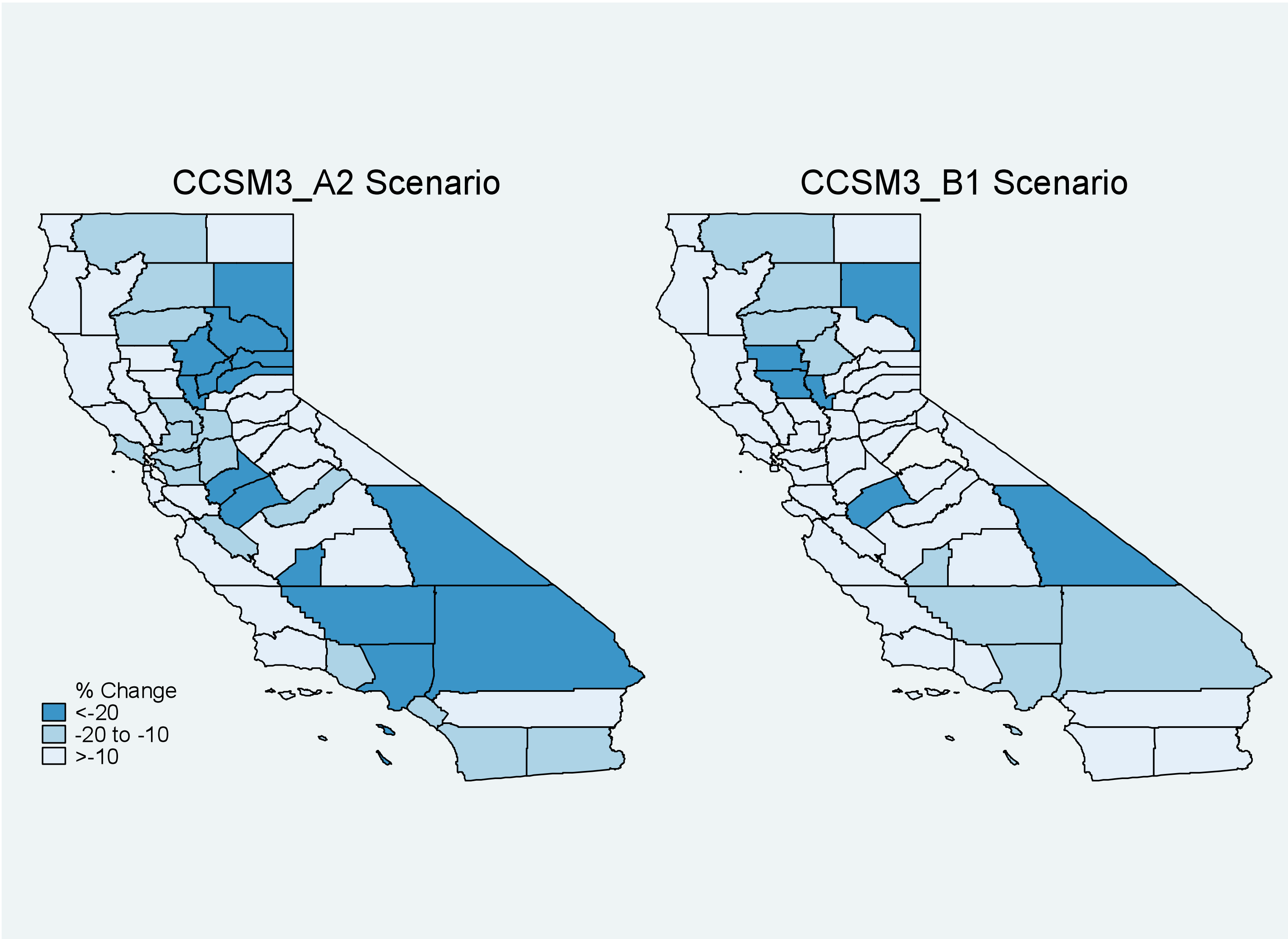

CCSM3_A2 Scenario
CCSM3_B1 Scenario
% Change
<-20
-20 to -10
>-10

Figure 3b. Predicted change in annual precipitation, percentage change in 2070–2099 relative to the 1950–2005 baseline

Table 2. County-level summary statistics on farm revenues, expenditures, and profits, 1969–2002

	1969	1974	1987	1992	1997	2002
Aggregate state totals						
Acres of Farmland (Mil.)	35.71	32.86	30.60	28.98	27.70	27.58
Total Sales ($Mil.)	21,270.4	24,834.7	21,996.0	22,884.7	28,037.5	28,794.9
Production Expenditures ($Mil.)	19,472.5	20,599.7	17,387.9	18,628.7	20,545.8	22,965.9
Total Profit ($Mil.)	1,797.9	4,235.1	4,608.1	4,255.9	7,491.8	5,829.0
County averages						
Sales ($Mil.)	379.8	428.2	372.8	387.9	475.2	496.5
Production Expenditures ($Mil.)	347.7	355.2	294.7	315.7	348.2	396.0
Profits ($Mil.)	32.1	73.0	78.1	72.1	127.0	100.5
Profits Per Acre (1$/acre)	50.3	128.9	150.6	146.9	270.5	211.4

Notes: Averages are calculated for a balanced panel of 58 counties over 6 census years (1969, 1974, 1987, 1992, 1997, 2002). All dollar values are in 2006 constant dollars.

Table 3. County average yields and value of production for 15 of the largest value crops in California, 1980–2005

	County Averages:				
Crop	**Counties**	**Yield**	**Total value ($ Mil.)**	**Dollar per acre**	**State total value ($ Mil.)**
Almonds	18.8	0.59	61.1	2,057.4	1,148.8
Avocados	11.0	2.80	30.1	4,707.2	332.2
Broccoli	12.6	5.93	37.4	3,941.8	470.2
Cotton	9.4	5.51	177.4	1,366.0	1,657.6
Grapes (non-wine)	14.7	6.62	110.1	4,787.7	1,618.0
Hay	51.4	4.34	23.0	534.0	1,179.4
Lemons	11.5	13.44	32.2	6,819.1	383.3
Lettuce	15.4	13.80	82.9	5,534.9	1,278.0
Oranges	12.8	10.90	81.2	4,779.6	1,039.9
Pistachios	9.6	0.87	22.3	3,059.8	213.6
Rice	15.7	3.12	35.1	994.3	552.4
Strawberries	14.3	22.34	52.9	27,070.2	752.2
Tomatoes	22.0	24.00	42.8	5,583.7	942.5
Walnuts	32.7	1.09	12.4	1,636.8	405.6
Wine Grapes	30.1	5.11	49.6	3,457.6	1,489.7
Total	---	---	---	---	13,463.4

Notes: Averages are calculated for a balanced panel of 58 counties over the years 1980–2005. All dollar values are in 2006 constant dollars.

The first column reports the average number of counties producing each crop. The most geographically widely produced crop is hay, produced in 51 counties, while the least geographically covered crop is cotton, which is grown in 9 counties on average. The yield (in tons per acre planted) is next reported. Tomatoes and strawberries are the highest yielding crops, while almonds and pistachios are the lowest yielding. There is important heterogeneity across crops in yields, which range from 0.6 to 24.0. Next are total value of production (in millions of dollars) and dollars per acre planted. (These and all subsequent figures are reported in 2006 constant dollars, unless noted otherwise.) The dollar yields per acre also exhibit a wide range, from $500 per acre planted for hay to $27,000 for strawberries. Finally, the last column shows the state total value of production for each crop, averaged over the 1980–2005 period. During this period, the highest value crops are grapes (wine and non-wine), hay, lettuce, almonds, oranges, and cotton, with each exceeding a value of $1 billion. Below we evaluate how climate change will impact the value of annual production of each of these crops.

5.0 Results

5.1. Estimates

This section reports our estimates of the economic impact of climate change on agricultural profits and yields. Before turning to these estimates, we begin with Figure 4a, which presents a simple graphical analysis of the relationship between profits per acre and weather—annual degree-days and precipitation. The figure plots the results from three separate regressions (Equation 1) for county-level profits per acre, all of which are weighted by total county-level agricultural acres. The line "OLS, Deciles" plots the predicted profit using ordinary least squares (OLS) parameter estimates and right-hand-side variables for deciles of the distribution of annual weather degree-days at the midpoint of each decile's range. This regression also includes year-fixed effects and soil variables. The next line, labeled "FE, Deciles" corresponds to the same model, with the addition of county fixed effects (FE), which takes into account climate and other differences from one county to another. The final line, labeled "FE, Quadratic," replaces degree-day decile indicators with a quadratic in degree-days and plots the conditional means at the midpoints of each decile's range.

There are a few important findings in this graph. First, in the "OLS, Deciles" line there is tremendous variation in profits per acre as it ranges from -$192 per acre to over $72 per acre. Notably, it is generally increasing throughout the range of the degree-days distribution. The addition of county fixed effects to the specification (the "FE, Deciles" line) greatly reduces the variation in profits per acre. The profits per acres on this line range from $10 to $100 per acre. We also observe that the modeling of degree-days with a quadratic provides a good approximation to the less parametric approach. Fourth, and most importantly, all models show that even relatively large increases in degree-days are unlikely to have negative effects on profits per acre (recall that the A2 scenario predicts increases of up to 1,000 annual degree-days).

One reason the OLS graph slopes upwards much more significantly is that differences in climate are only reflected in differences in weather–there are no climate variables or fixed effects. When fixed effects are introduced, these fixed effects capture climate differences. Different climates involve different agricultural practices, which reduce the effect of weather anomalies. This is seen in the FE graphs in Figure 4a.

Figure 4b repeats this analysis for annual precipitation. All lines in this case are downward-sloping, indicating a negative relationship between profits per acre and annual precipitation, which possibly reflects our inadequate controls for water supplied by irrigation (even though the soil characteristics variables include the fraction of farmland that is irrigated in each county. After adjustment for the county fixed effects however, the response surfaces are relative flat above the sample mean of 50 centimeters of annual rainfall (to the right of the vertical line). Again, this analysis suggests that small reductions or increases in annual precipitations are unlikely to have dramatic effects on agricultural profits; furthermore, a decrease in precipitation is unlikely to decrease profits.

Table 4 shows the basic estimation results with annual weather/climate variables, although results for only weather and climate independent variables are shown. Estimation results for models with seasonal weather are not shown. There are three basic annual weather/climate models, two variants of Equation 1 and one variant of Equation 2. What varies from one model to the next is indicated at the bottom of Table 4. Because of problems identifying climate effects separately from fixed effects, county fixed effects are omitted from estimates of Equation 2. Significance of individual parameters is not always strong, though covariance between parameter estimates generally leads to significance of the group of climate variables and significance of the group of weather variables. This will become clearer as we look at the significance of profit changes.

Note from the results in column (3) that increases in expected or average degree days has a significantly positive effect on profits, whereas degree days 32°C or warmer do not, nor does precipitation. On the other hand, realizations of the weather have a different effect, reflecting the fact, for example, that a hot day when you are expecting a cool day is different from a hot day when you are expecting a hot day. Presumably, crops can be tailored to the local climate more easily than crops can be made resilient to unexpected weather deviations. Degree days 32°C or warmer in terms of weather have a significantly negative effect on profit—actual hot weather reduces profit.

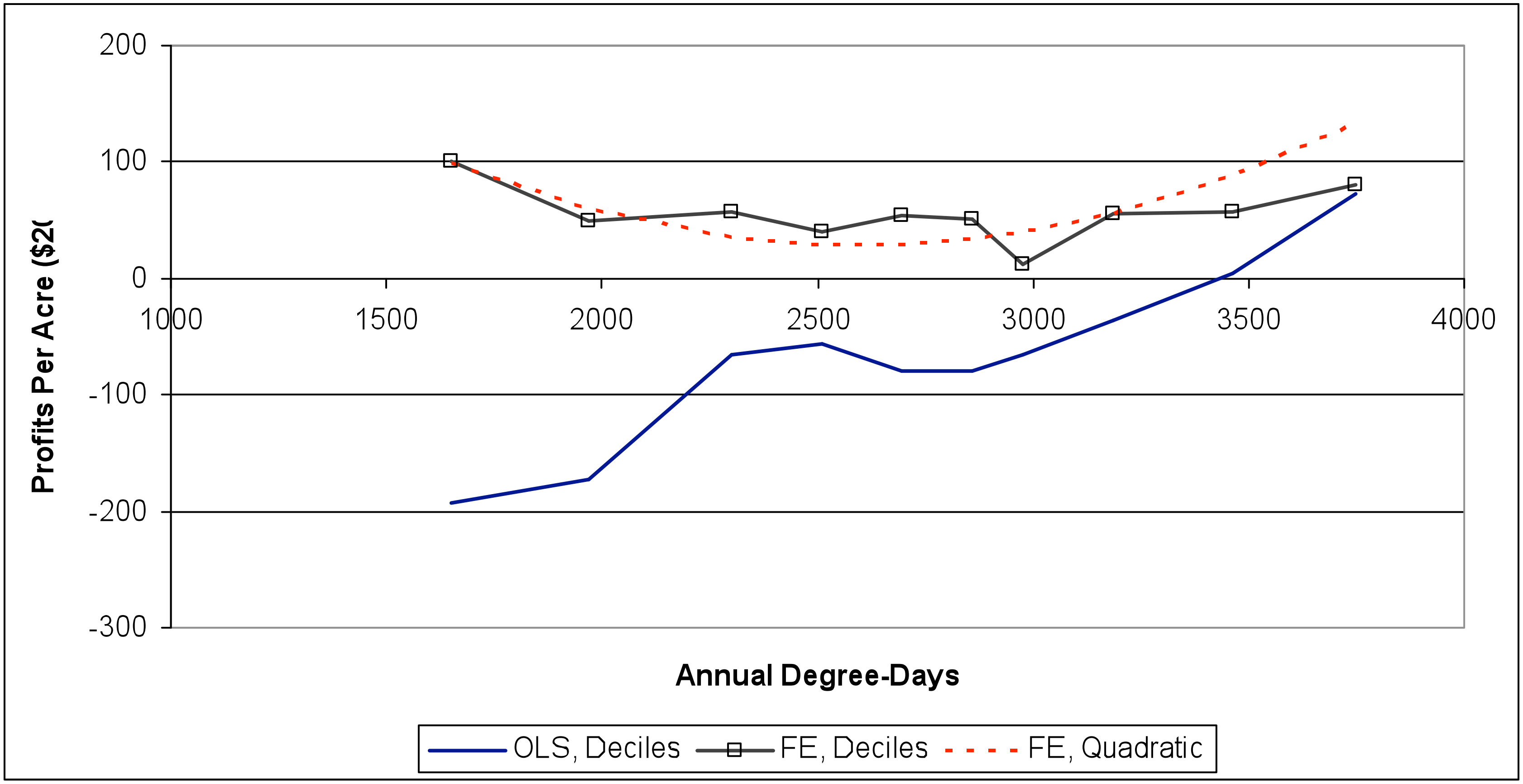


Figure 4a. Estimated relationship between annual degree-days (base 8°C–32°C) and profits per acre, 1987–2002

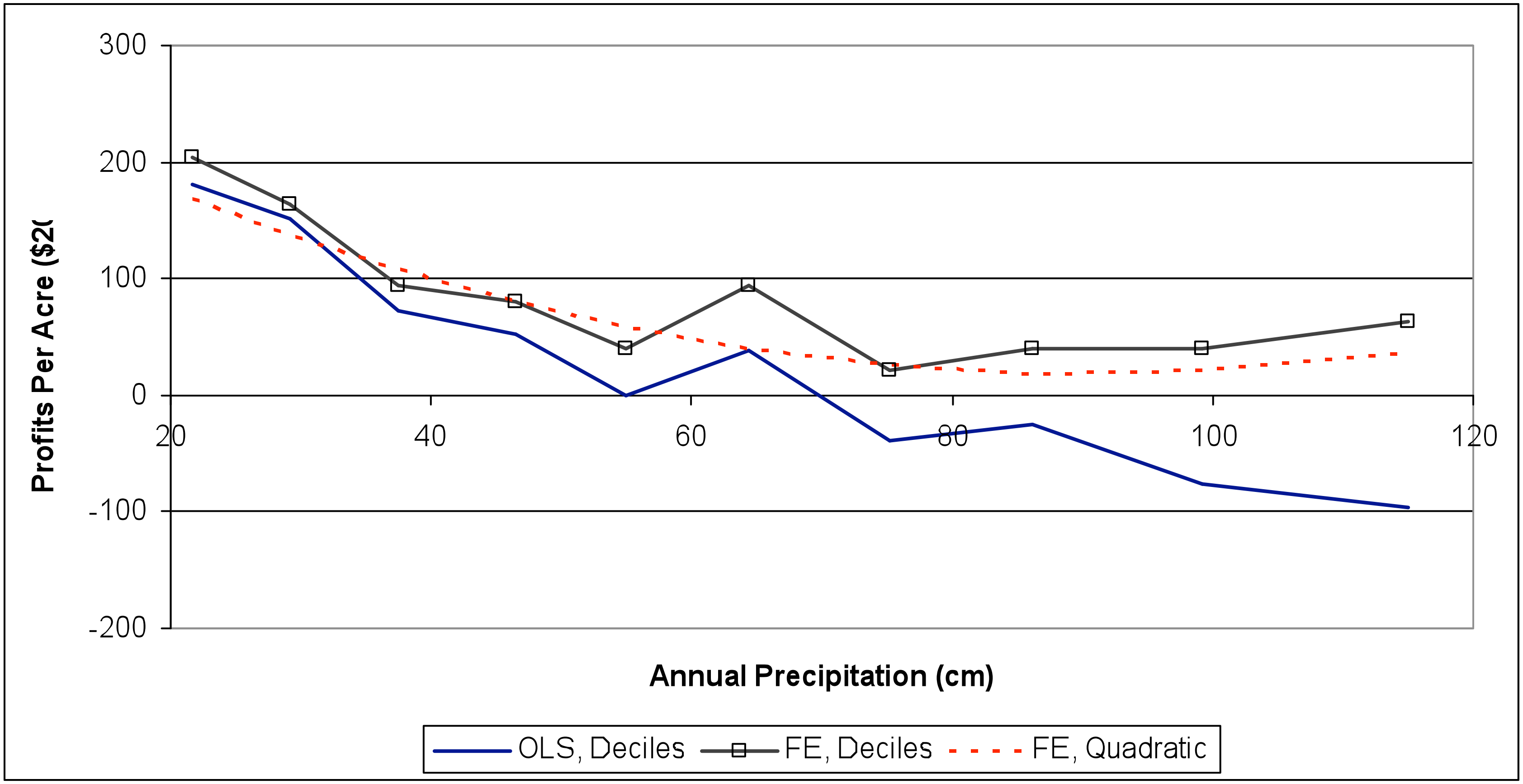


Figure 4b. Estimated relationship between annual precipitation and profits per acre, 1987–2002

Table 4. Estimation results for key independent variables, equations 1 and 2 with annual weather/climate (standard errors in parentheses)

	Equation (1) -- weather only		Equation (2) -- weather and climate
	(1)	(2)	(3)
Weather Variables			
Degree Days (8-32)	0.0871	0.0480	0.0353
	(0.0292)	(0.0373)	(0.0301)
Degree Days (32+)	-1.6403	-1.2789	-1.5272
	(0.5589)	(0.4376)	(0.4570)
Precipitation	-1.7692	-0.9268	-1.5488
	(0.5595)	(0.9208)	(0.8413)
Climate Variables			
Degree Days (8-32)	---	---	0.0691
			(0.0351)
Degree Days (32+)	---	---	-0.5987
			(0.9815)
Precipitation	---	---	-0.2237
			(0.9142)
R-squared	0.369	0.654	0.375
County fixed-effects	No	Yes	No
Year effects	Yes	Yes	Yes
Soil characteristics	Yes	Yes	Yes
Number of explanatory variables	16	73	19
Observations	343	343	343

Note: Degree-Days 8-32 denotes Degree-Days 8°C–32°C and Degree-Days 32+ denotes Degree-Days 32°C+

5.2. Future Climate Change

Tables 5 to 7 present estimates of the impact of the A2 and B1 climate change scenarios on annual agricultural profits (Equation 3). These results are derived from the estimation of versions of Equations 1 and 2.

Table 5a presents our first set of impact projections for aggregate agricultural profits. These projections are based on the A2 scenario and on the estimation of models nested in Equation 1. Namely, we consider models that control only for annual degree-days and precipitation, rather than their seasonal values, to which we return in a subsequent table. Given the relatively small estimating sample (343 county-year observations), this restriction helps preserve degrees of freedom and focus the analysis of a small set of explanatory variables.

The first panel shows the projections over the period 2010–2039, the second panel reports the projections over the 2040-2069 period, and the last panel reports projections for the 2070–2099 period. The first column of each panel reports estimates based on OLS estimation of Equation 1 with linear controls for annual degree-days (both 8°C–32°C and 32°C+) and precipitations. Estimate in the second columns are based on models that include county fixed effects. In each column we can also decompose the impact into its component due to change in the distribution of daily temperatures and the distribution of precipitations. In addition, the standard errors associated with each point estimate are reported in parentheses. Other specification details are noted at the bottom of the table.

Note from Table 5a that the impact of the annual degree-days depends dramatically on the inclusion or exclusion of county fixed effects. In general, in models with county fixed effects, degree-days are not significantly associated with change in agricultural profits, while they are in the OLS models (the one exception are the projections on the 2010–2039 horizon). This is consistent with the discussion of Figure 4a where we argued that climate is included in the fixed effect and thus including or excluding fixed effects makes a big difference when climate is not an explicit regression.

Taken as a whole, the information in Table 5a reveals three keys points: (1) The impact of climate change on agricultural profits in California is likely to be positive, although the exact magnitude varies. In percentage term, the impacts range from 4.0% to 36.4%, with larger changes in later years. In absolute terms, the aggregate profits are projected to increase by 0.2 to 2.2 billion of 2006 dollars. The entries in Table 5a also indicate the impacts are projected to grow over time: the long-run impacts (2070–2099) generally exceed the medium-run (2040–2069) and short-term (2010–2039) impacts. Second, across all specifications the impact of the reduction in annual precipitations on profits is positive and statistically significant, with impacts ranging from $168 million to $381 million. This somewhat counterintuitive result might reflect our inability to adequately control for the supply of water available to farmers (e.g., Schlenker, Hanemann, Fisher 2007), despite the fact that all our models include controls for the fraction of farmland in a county that is irrigated.

Table 5b replicates 5a, but for the predictions scenario B1. Since the B1 scenario predicts smaller increases in temperature, and smaller reductions (or increases) in precipitations, the resulting impacts on profits are smaller in magnitude than those reported in Table 5a. The long-term impacts range from 5.2% to 15.8% change in annual profits.

Tables 6a and 6b present climate change projections derived from statistical models that are more general than those discussed so far. As before, the "a" table refers to scenario A2 and the "b" table to scenario B1. In both tables, we now break down the annual degree-days into seasonal degree-days (total degree-days during the winter, spring, summer, and fall). We do the same for annual precipitation. This leads to a less parsimonious statistical model (with fewer degrees of freedom), but one that is probably better-suited for California's agriculture, as several crops are grown all year-round.

In terms of the B1 scenario, Table 6b presents the mirror image of 6a, with the exception that the impacts are smaller in magnitude as was noted before. In this case, the range of long-term profit impacts, is -2.4% to 35.6%, approximately five times smaller than what was reported in Table 6a.

Tables 7a and 7b are based on the estimation of models that derive from versions of Equation 2. This is our preferred model. The main difference is that models now include controls for realized weather in a given year, as well as our 30-year running average of the weather realizations, which we refer to as "climate." The key point is that these "climate" variables provide a proxy measure for farmers' expectations about the weather. However, the inclusion of these variables, which evolve slowly and smoothly, make it difficult to estimate the unrestricted version of Equation 2, because of degree of collinearity between the county fixed-effects, the time fixed-effects, and the "climate" variables. As such, we omit county fixed-effects from Tables 7a and 7b and focus on OLS estimation only. In addition, we only report the models that control for annual degree-days and precipitations. As we showed above, the aggregate impacts are not significantly altered when we break down the weather variables in their seasonal values.

The results in Table 7a lead to the same qualitative conclusion that climate change is not likely to lead to an important reduction in agricultural profits in California. The aggregate impacts are positive across all specifications in Table 7a. As expected, the magnitude of the impacts grows with the time horizon of the projection. Over the 2070–2099 period, the projected impact is +2.3 billions of dollars, or 41%. In addition, the confidence intervals around the estimated impacts are bounded away from 0, so we can rule out zero of negative impacts. The positive impacts are mostly attributable to the increase in degree-days in the A2 scenario. While large in magnitude, the climate effects are generally statistically insignificant.

Table 5a. Predicted impacts for scenario A2: OLS and FE estimates of agricultural profits in California (million of 2006 dollars); estimated equation 1, weather only

	Projected Impact: 2010-2039		**Projected Impact: 2040-2069**		**Projected Impact: 2070-2099**	
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Impact on Profits ($2006 Mil.)	**219.6**	**460.9**	**1,362.8**	**664.5**	**2,018.9**	**882.6**
	(174.7)	**(79.0)**	**(364.9)**	**(582.1)**	**(822.0)**	**(1221.7)**
Percent effect	*4.0*	*8.3*	*24.6*	*12.0*	*36.4*	*15.9*
Due to temperature change	51.5	140.0	981.7	464.8	1,734.5	733.6
	(119.3)	(82.5)	(423.5)	(592.3)	(875.5)	(1251.8)
Due to precipitation change	168.1	320.9	381.1	199.7	284.4	149.0
	(167.0)	(101.5)	(120.5)	(198.4)	(90.0)	(148.0)
F-Statistics (p-values)						
Temperature variables	0.001	0.849	0.001	0.849	0.001	0.849
Precipitation variables	0.001	0.029	0.001	0.029	0.001	0.029
County fixed-effects	No	Yes	No	Yes	No	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Soil characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Number of explanatory variables	16	73	16	73	16	73
Observations	343	343	343	343	343	343

Table 5b. Predicted impacts for scenario B1: OLS and FE estimates of agricultural profits in California (million of 2005 dollars); estimated equation 1, weather only

	Projected Impact: 2010-2039		Projected Impact: 2040-2069		Projected Impact: 2070-2099	
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Impact on Profits ($2006 Mil.)	**591.7**	**289.1**	**656.9**	**320.1**	**876.4**	**427.4**
	(109.7)	**(216.7)**	**(242.2)**	**(344.8)**	**(351.3)**	**(489.5)**
Percent effect	*10.7*	*5.2*	*11.8*	*5.8*	*15.8*	*7.7*
Due to temperature change	301.1	136.9	603.7	292.2	858.6	418.1
	(138.0)	(195.0)	(251.6)	(349.5)	(354.6)	(491.3)
Due to precipitation change	290.5	152.2	53.3	27.9	17.9	9.4
	(91.9)	(151.2)	(16.8)	(27.7)	(5.6)	(9.3)
F-Statistics (p-values)						
Temperature variables	0.001	0.849	0.001	0.849	0.001	0.849
Precipitation variables	0.001	0.029	0.001	0.029	0.001	0.029
County fixed-effects	No	Yes	No	Yes	No	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Soil characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Number of explanatory variables	16	73	16	73	16	73
Observations	343	343	343	343	343	343

Table 6a. Predicted impacts for scenario A2: OLS and FE estimates of agricultural profits in California (million of 2005 dollars); estimated equation 1, seasonal weather only

	Projected Impact: 2010-2039		Projected Impact: 2040-2069		Projected Impact: 2070-2099	
	(1)	(2)	(1)	(2)	(1)	(2)
Impact on Profits ($2006 Mil.)	**-498.1**	**62.7**	**3,602.0**	**3,877.6**	**9,627.5**	**9,883.0**
	(316.1)	**(352.5)**	**(478.4)**	**(651.1)**	**(1242.1)**	**(1090.9)**
Percent effect	*-9.0*	*1.1*	*64.9*	*69.9*	*173.6*	*178.2*
Due to temperature change	**-576.9**	**-58.3**	**3,578.1**	**3,817.1**	**9,651.4**	**9,839.9**
	(298.3)	**(311.5)**	**(507.2)**	**(601.6)**	**(1277.3)**	**(1079.8)**
Due to winter temperature change	90.0	65.0	1,083.4	782.2	2,683.5	1,937.4
	(50.4)	(60.3)	(606.7)	(726.0)	(1502.7)	(1798.2)
Due to spring temperature change	195.9	-95.4	995.5	-478.6	2,249.5	-996.9
	(221.3)	(295.8)	(1123.2)	(1500.7)	(2519.2)	(3357.7)
Due to summer temperature change	-874.9	-54.9	-1,952.3	-165.5	-4,086.0	-579.1
	(445.2)	(450.8)	(947.6)	(968.8)	(1739.7)	(1830.6)
Due to fall temperature change	12.1	27.0	3,451.6	3,679.1	8,804.3	9,478.5
	(95.9)	(138.4)	(832.7)	(951.1)	(1671.3)	(1633.9)
Due to precipitation change	**78.7**	**121.0**	**23.9**	**60.5**	**-23.9**	**43.1**
	(82.4)	**(164.0)**	**(130.6)**	**(246.5)**	**(137.3)**	**(222.9)**
Due to winter precipitation change	164.2	169.4	138.3	142.7	147.1	151.7
	(95.1)	(143.8)	(80.1)	(121.1)	(85.2)	(128.7)
Due to spring precipitation change	-19.9	-8.0	66.9	26.8	39.8	15.9
	(13.5)	(14.6)	(45.4)	(49.0)	(27.0)	(29.1)
Due to summer precipitation change	-34.8	-20.5	-140.8	-82.7	-198.6	-116.7
	(22.8)	(26.3)	(92.4)	(106.3)	(130.3)	(149.9)
Due to fall precipitation change	-30.7	-20.0	-40.5	-26.3	-12.1	-7.9
	(68.3)	(95.3)	(90.0)	(125.6)	(27.0)	(37.7)
F-Statistics (p-values)						
Temperature variables	0.001	0.001	0.001	0.001	0.001	0.001
Precipitation variables	0.043	0.704	0.043	0.704	0.043	0.704
County fixed-effects	No	Yes	No	Yes	No	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Soil characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Number of explanatory variables	22	79	22	79	22	79
Observations	343	343	343	343	343	343

Table 6b. Predicted impacts for scenario B1: OLS and FE estimates of agricultural profits in California (million of 2006 dollars); estimated equation 1, seasonal weather only

	Projected Impact: 2010-2039		Projected Impact: 2040-2069		Projected Impact: 2070-2099	
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Impact on Profits ($2006 Mil.)	**882.3**	**-132.3**	**1,050.0**	**184.2**	**1,975.7**	**434.0**
	(252.7)	**(348.4)**	**(274.3)**	**(279.0)**	**(454.4)**	**(505.9)**
Percent effect	*15.9*	*-2.4*	*18.9*	*3.3*	*35.6*	*7.8*
Due to temperature change	**1,056.3**	**-85.3**	**991.1**	**157.3**	**2,161.2**	**480.7**
	(217.5)	**(252.6)**	**(279.0)**	**(301.6)**	**(459.1)**	**(485.0)**
Due to winter temperature change	279.2	184.9	698.0	462.0	936.3	619.9
	(156.4)	(182.2)	(390.8)	(455.5)	(524.3)	(611.1)
Due to spring temperature change	397.1	-217.4	682.3	-372.9	767.6	-419.5
	(453.5)	(602.7)	(774.4)	(1034.0)	(870.9)	(1163.3)
Due to summer temperature change	-848.1	-170.8	-1,240.1	-209.6	-1,705.3	-297.4
	(416.3)	(399.9)	(633.1)	(600.1)	(864.9)	(821.4)
Due to fall temperature change	1,228.1	118.0	851.0	277.7	2,162.5	577.7
	(200.3)	(178.0)	(299.1)	(418.8)	(632.5)	(871.3)
Due to precipitation change	**-174.0**	**-47.0**	**58.9**	**27.0**	**-185.5**	**-46.7**
	(164.1)	**(227.1)**	**(27.7)**	**(40.8)**	**(114.8)**	**(107.5)**
Due to winter precipitation change	73.3	64.1	17.8	15.5	38.0	33.2
	(42.5)	(64.5)	(10.3)	(15.7)	(22.0)	(33.4)
Due to spring precipitation change	-64.1	-18.6	42.3	12.2	-136.3	-39.5
	(43.5)	(46.6)	(28.7)	(30.7)	(92.4)	(99.0)
Due to summer precipitation change	-130.2	-60.0	0.9	0.4	-85.1	-39.2
	(85.4)	(99.0)	(0.6)	(0.7)	(55.8)	(64.7)
Due to fall precipitation change	-53.0	-32.6	-2.0	-1.2	-2.1	-1.3
	(117.8)	(163.6)	(4.5)	(6.3)	(4.6)	(6.4)
F-Statistics (p-values)						
Temperature variables	0.001	0.001	0.001	0.001	0.001	0.001
Precipitation variables	0.043	0.704	0.043	0.704	0.043	0.704
County fixed-effects	No	Yes	No	Yes	No	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Soil characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Number of explanatory variables	22	79	22	79	22	79
Observations	343	343	343	343	343	343

Table 7a. Predicted impacts for scenario A2: OLS estimates of agricultural profits in California (million of 2006 dollars); estimated equation (2), annual weather and climate

	Projected Impact: 2010-2039	Projected Impact: 2040-2069	Projected Impact: 2070-2099
	(1)	**(1)**	**(1)**
Impact on Profits ($2006 Mil.)	**478.7**	**1,527.7**	**2,272.7**
	(89.5)	**(367.1)**	**(824.4)**
Percent effect	*8.6*	*27.5*	*41.0*
Due to temperature change	157.2	1,145.9	1,987.8
	(83.8)	(424.4)	(879.7)
Annual temperature effect	-1.9	224.1	194.7
	(104.8)	(502.3)	(1083.3)
Climate effect	159.1	921.8	1,793.1
	(107.1)	(518.1)	(1103.1)
Due to precipitation change	321.5	381.9	285.0
	(112.0)	(133.1)	(99.3)
Annual precipitation effect	280.9	333.7	249.0
	(152.6)	(181.2)	(135.2)
Climate effect	40.6	48.2	36.0
	(165.8)	(196.9)	(147.0)
F-Statistics (p-values)			
Temperature variables	0.001	0.001	0.001
Precipitation variables	0.071	0.071	0.071
County fixed-effects	No	No	No
Year effects	Yes	Yes	Yes
Soil characteristics	Yes	Yes	Yes
Number of explanatory variables	19	19	19
Observations	343	343	343

Table 7b. Predicted impacts for scenario B1: OLS estimates of agricultural profits in California (million of 2006 dollars); estimated equation 2, annual weather and climate

	Projected Impact: 2010-2039	Projected Impact: 2040-2069	Projected Impact: 2070-2099
	(1)	**(1)**	**(1)**
Impact on Profits ($2006 Mil.)	**640.2**	**760.7**	**1,025.0**
	(115.1)	**(242.8)**	**(352.5)**
Percent effect	*11.5*	*13.7*	*18.5*
Due to temperature change	349.1	707.3	1,007.1
	(138.2)	(252.5)	(355.9)
Annual temperature effect	55.6	152.5	222.5
	(166.8)	(294.8)	(413.8)
Climate effect	293.5	554.9	784.5
	(170.7)	(306.1)	(430.7)
Due to precipitation change	291.1	53.4	17.9
	(101.4)	(18.6)	(6.2)
Annual precipitation effect	254.4	46.6	15.6
	(138.2)	(25.3)	(8.5)
Climate effect	36.7	6.7	2.3
	(150.1)	(27.5)	(9.2)
F-Statistics (p-values)			
Temperature variables	0.001	0.001	0.001
Precipitation variables	0.071	0.071	0.071
County fixed-effects	No	No	No
Year effects	Yes	Yes	Yes
Soil characteristics	Yes	Yes	Yes
Number of explanatory variables	19	19	19
Observations	343	343	343

5.3. Specific Crops

We have also explored the effect of predicted climate change on the value of crops produced in California. Based on the Census of Agriculture data for 1987–2002, crop sales represent about 70% of total farm sales in California. Crops are important, but sales of livestock and dairy products are also important.

Another motivation for examining individual crops yields is to assess the limitations of the profits approach we propose in the paper. Large declines in yields would suggest that the profit results may be biased (relative to the preferred long run measure) by short run price increases. Although farmers cannot switch crops in response to weather shocks, they are able to undertake some adaptations, although not to the same extent as it is possible in response to permanent climate change.

The analysis is based on the 15 largest-grossing crops (perennials and annuals) in California. Summary statistics on these were displayed in Table 3. The analysis is based on the estimation of Equation 2, where the dependent variables are county-level value of production per acre planted, for each of the 15 crops. The regressions all include controls for soil characteristics and year fixed effects and are weighted by the square root of the number of acres planted in each crop. The independent variables of interest are the seasonal degree-days and precipitation, but in terms of realized weather and its long-run averages (climate). For the reasons discussed above, estimation is performed using OLS (i.e., excluding county fixed effects).

The results are presented graphically in Figure 5, which shows the percentage impacts for each crop, associated with the prediction of CCSM3, scenario A2. Percentage impacts are computed by norming the predicted change in value of production for each crop by the historical average value of production for each of the crops. The figure reports the point estimates (the red square) and its 95% confidence interval (delimited by the horizontal bars). The main message of Figure 5 is that climate change will have a heterogeneous impact on value of production in California. For some crops, the value of production is projected to increase by as much as 20% (i.e., cotton, hay, lettuce), while for others (i.e., lemons, food grapes), the value of production is projected to decrease by 20% or more .

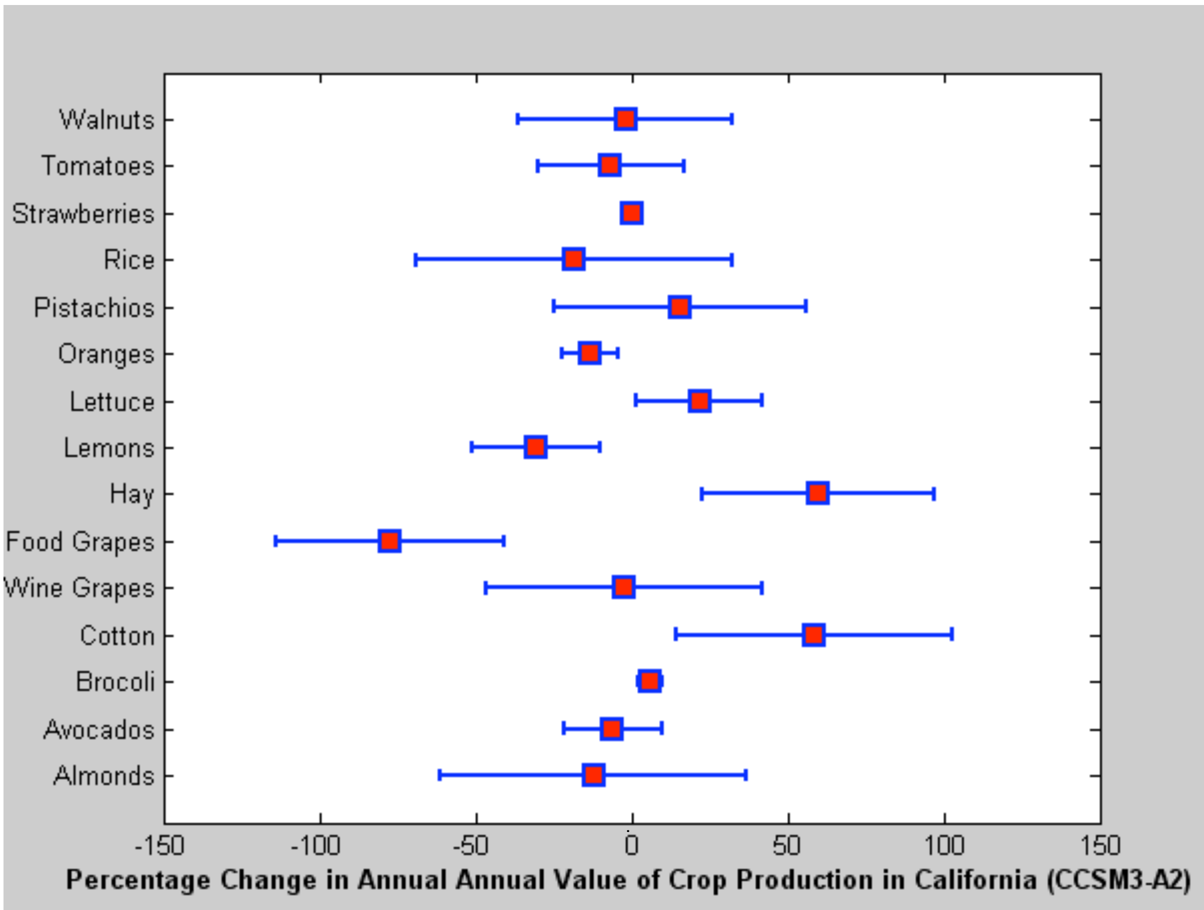
Taken as a whole, the evidence in Figure 5 fails to deliver a statistically significant relationship between climate change and crop yields for most of the crops. As such, the small changes in output or quantities suggest that it is unlikely that the previous subsection's finding that climate change will have a small effect on agricultural profits is due to short-run price increases.

5.4. Caveats

There are a number of caveats to this analysis and calculations. First, the analysis ignores extreme events (e.g., droughts and floods) or the variance of climate realizations, in addition to any effects on degree-days and precipitation. So it is uninformative about the economic impact of these events. Similarly, it is possible that climate change will disrupt local ecosystems and/or change soil quality. Both of these factors may affect agricultural productivity. Since annual fluctuations in climate are unlikely to have the same effect on ecosystems and soil quality as permanent changes, our estimates fail to account for these effects too.

Second, global climate change will likely affect agricultural production around the world, which will cause changes in relative prices. Although our estimates are based on annual fluctuations in weather and are adjusted for year fixed effects, we are not able to account fully for future price changes.

Third, our analysis is conditional on the existing system of government programs that impact agricultural profits and land values by affecting farmers' decisions about which crops to plant, the amount of land to use, and the level of production (Kirwan 2005). Our estimates would likely differ if they were estimated with an alternative set of subsidy policies in place.



Notes: Results from estimation of Equation 2 separately for each of indicated crops. Weather and climate are annual data. Error bars reflect 95% confidence levels.

Figure 5. Predicted impacts of climate change on annual value of crop production, scenario A2, 2070–2099 (percentage impacts relative to a 1980–2005 baseline)

Finally, we discuss three issues with our approach that can cause it to yield and incorrect prediction of the damage associated with climate change. First, we emphasize that these projections are conditional on the current prices and availability of water for irrigation. In the likely event that these factors change over the next century, our approach is unlikely to correspond to the true future sequence of agricultural profits. In addition, elevated carbon dioxide (CO_2) concentrations are known to increase the yield per planted acre for many plants (see e.g., Miglietta et al. 1998). Since higher CO_2 concentrations are thought to be a primary cause of climate change, it possible that carbon fertilization will lead to higher yields per acre, which in turn would affect agricultural profits, something not accounted for in our analysis. Finally, our representation of how weather and climate affect profits is admittedly simple, in part because of the limited data available to us for estimation.

6.0 Conclusions

The question posed in this paper is: what does the historic record tell us about how agriculture in California will be affected by climate change? Although there are limitations to our analysis that prevent us from being too specific in answering this question, there are two tentative conclusions.

One conclusion is that climate change may in fact result in increased farm profits in the state, though obviously not for all farms. A second and related conclusion is that different crops will be affected very differently. Profits from table grapes, for instance, are expected to decline significantly, whereas profits from hay should increase, at least in percentage terms (of course, grapes generate more profit per acre than hay).

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